An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Make a Big Difference?

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Dropping data: Mexico Microcredit

Example: Angelucci et al. [2015], a randomized controlled trial study of the efficacy of microcredit in Mexico based on N =16,560 data points. A regression was run to estimate the average effect of microcredit.

Original result: Treatment effect statistically insignificant at 95%.

Policy implication: Disinvest in microcredit initiatives.

Data dropping: Can produce both positive and negative statististically significant results dropping no more than 15 data points ($< 0.1\%$).

Policy implication: Run a higher-powered study (not just larger N).

Cannot find influential subsets by brute force!

We provide a fast, automatic tool to approximately identify the most influential set of points.

Outline

- Why and when might you care about sensitivity to data dropping?
- How do we identify influential sets? When is our method accurate?
  (A formalization of the problem and the class of estimators we study.)
- Examine real-life examples of analyses: some sensitive, some not.
  (The results may defy your intuition.)
- What kinds of analyses are sensitive to data dropping?
  (Including comparison to standard errors and how improve data dropping robustness.)

Dropping data: Motivation

When and why do you care that you can **reverse your conclusion** by removing a **small proportion** of your data?

Not always! But sometimes, surely yes, especially when you want to **generalize to unseen, systematically different populations**.

Suppose you have a farm, and want to know whether your average yield is $>$ 170 bushels per acre. At harvest, you measure 200 bushels per acre.

- Scenario one: $>$ 170 bushels per acre means you make a profit.
    - Don't care about sensitivity to small subsets.
- Scenario two: Want to recommend methods to a distant friend.
    - Might care about sensitivity to small subsets!

Specifically, often in statistical applications:

- Policy population is different from analyzed population,
- Small fractions of data are missing not-at-random,
- We report a convenient summary (e.g. mean) of a complex effect.

Formalizing the question.

Ordinary least squares

A data point d_n has regressors x_n and response y_n: $d_n = (x_n, y_n)$.

The estimator $\hat{\theta} \in \mathbb{R}^P$ satisfies:

$$\hat{\theta} := \arg\min_{\theta} \frac{1}{2} \sum_{n=1}^{N} \left(y_n - \theta^T x_n\right)^2$$

$$\Leftrightarrow \sum_{n=1}^{N} \left(y_n - \hat{\theta}^T x_n\right) x_n = 0.$$

Make a qualitative decision using:

- A particular component: $\hat{\theta}_k$
- The end of a confidence interval: $\hat{\theta}_k + \frac{1.96}{\sqrt{N}} \hat{\sigma}(\hat{\theta})$

Z-estimators

We observe N data points $d_1, \ldots, d_N$ (in any domain).

The estimator $\hat{\theta} \in \mathbb{R}^P$ satisfies:

$$\sum_{n=1}^{N} G(\hat{\theta}, d_n) = 0_P.$$

$G(\cdot, d_n)$ is "nice," $\mathbb{R}^P$-valued. E.g. OLS, MLE, VB, IV &c.

Make a qualitative decision using $\phi(\hat{\theta})$ for a smooth, real-valued ϕ.

(WLOG try to increase $\phi(\hat{\theta})$.)

Data dropping as data reweighting.

Question: Can we make a big change in $\phi(\hat{\theta})$ by dropping $\lfloor \alpha N \rfloor$ datapoints, for some small proportion α? **Two big problems:**

- There are $\binom{N}{\lfloor \alpha N \rfloor}$ sets to check. (E.g. $\binom{16{,}560}{15} \approx 1.5 \cdot 10^{51}$)
- Evaluating $\hat{\theta}$ re-solving the estimating equation.
  - E.g., re-computing the OLS estimator.
  - Other examples are even harder (VB, machine learning)

Our idea: Smoothly approximate the effect of leaving out points.

We have N data points $d_1, \ldots, d_N$, a quantity of interest $\phi(\cdot)$, and

$$\sum_{n=1}^{N} G(\hat{\theta}, d_n) = 0_P \qquad .$$

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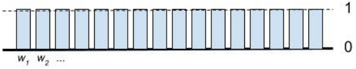
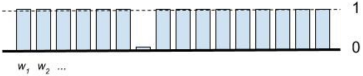
Original weights: $\vec{1} = (1, \ldots, 1)$



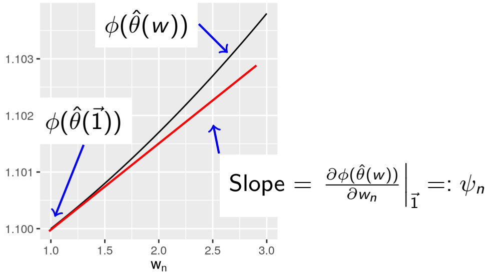
Leave points out by setting their elements of w to zero.



The map $w \mapsto \phi(\hat{\theta}(w))$ is well-defined even for continuous weights.

Taylor series approximation.

$$\sum_{n=1}^{N} w_n G(\hat{\theta}(w), d_n) = 0_P \text{ for a weight vector } w \in \mathbb{R}^N.$$



The values $N\psi_n$ are the **empirical influence function** [Hampel, 1986]. We call ψ_n an "influence scores."

We can use ψ_n to form a Taylor series approximation:

$$\phi(\hat{\theta}(w)) \approx \phi^{\text{lin}}(w) := \phi(\hat{\theta}(\vec{1})) + \sum_{n=1}^{N} \psi_n (w_n - 1)$$

Taylor series approximation.

Problem: How much can you change $\phi(\hat{\theta}(w))$ dropping $\lfloor \alpha N \rfloor$ points?
Combinatorially hard by brute force!

Approximate Problem: How much can you change $\phi^{\mathrm{lin}}(\hat{\theta}(w))$ dropping $\lfloor \alpha N \rfloor$ points? **Easy!**

$$\phi^{\mathrm{lin}}(w) := \phi(\hat{\theta}(\vec{1})) + \sum_{n=1}^{N} \psi_n (w_n - 1)$$

Dropped points have $w_n - 1 = -1$. Kept points have $w_n - 1 = 0$
$\Rightarrow$ The most influential points for $\phi^{\mathrm{lin}}(w)$ have the most negative ψ_n.

Our procedure: (see `rgiordan/zaminfluence` on `github`)

1. Compute your original estimator $\hat{\theta}(\vec{1})$.
2. Compute and sort the influence scores $\psi_{(1)}, \ldots, \psi_{(N)}$.
3. Worry if $-\sum_{n=1}^{\lfloor \alpha N \rfloor} \psi_{(n)}$ is large enough to change your conclusions.

How to compute the ψ_n's? And how accurate is the approximation?

How to compute the influence scores?

How can we compute the influence scores $\psi_n = \left.\frac{\partial \phi(\hat{\theta}(w))}{\partial w_n}\right|_{\vec{1}}$?

By the **chain rule**, $\psi_n = \left.\frac{\partial \phi(\theta)}{\partial \theta}\right|_{\hat{\theta}(\vec{1})} \left.\frac{\partial \hat{\theta}(w)}{\partial w_n}\right|_{\vec{1}}$.

Recall that $\sum_{n=1}^{N} w_n G(\hat{\theta}(w), d_n) = 0_P$ for all w near $\vec{1}$.

$\Rightarrow$ By the **implicit function theorem**, we can write $\left.\frac{\partial \hat{\theta}(w)}{\partial w_n}\right|_{\vec{1}}$ as a linear system involving $G(\cdot, \cdot)$ and its derivatives.

$\Rightarrow$ The ψ_n are automatically computable from $\hat{\theta}(\vec{1})$ and software implementations of $G(\cdot, \cdot)$ and $\phi(\cdot)$ using **automatic differentiation**.

```
> import jax
> import jax.numpy as np
> def phi(theta):
>     ... computations using np and theta ...
>     return value
>
> # Exact gradient of phi (first term in the chain rule above):
> jax.grad(phi)(theta_opt)
```

See `rgiordan/vittles` on `github`.

How accurate is the approximation?

Checking the approximation for Mexico microcredit.

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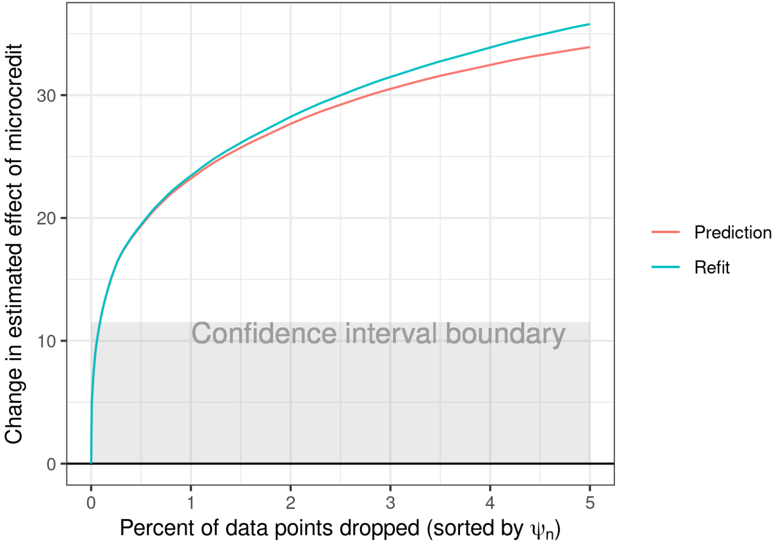
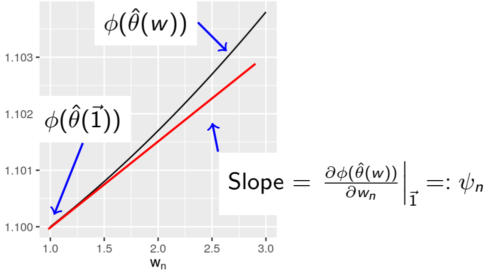


How accurate is the approximation?

By conrolling the curvature, we can control the error in the linear approximation.



We provide **finite-sample theory** [Giordano et al., 2019] showing that

$$\left|\phi(\hat{\theta}(w)) - \phi^{\mathrm{lin}}(w)\right| = O\left(\left\|\frac{1}{N}(w - \vec{1})\right\|_2^2\right) = O(\alpha) \text{ as } \alpha \to 0.$$

But you don't need to rely on the theory!

Our method returns which points to drop. **Re-running once** without those points provides an **exact lower bound** on the worst-case sensitivity.

Selected experimental results.

Original estimate (SE)	Refit estimate (SE)	Observations dropped
-4.549 (5.879)	7.030 (2.549)*	$15 = 0.09\%$

Table: Microcredit Mexico results ($N = 16560$) [Angelucci et al., 2015].

A $*$ indicates statistical significance at the 95% level.

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Table: Cash transfers results (N = 10518) [Angelucci and De Giorgi, 2009]

Original estimate (SE)	Refit estimate (SE)	Observations dropped
0.029 (0.005)*	-0.009 (0.004)*	224 = 0.96%

Table: Medicaid profit results (N = 23361) [Finkelstein et al., 2012]

A $*$ indicates statistical significance at the 95% level.

What makes an analysis sensitive? Preliminaries

We are **robust to data dropping** if, for the Δ that changes conclusions and w^* dropping the $\lfloor \alpha N \rfloor$ most influential points,

$$\Delta \geq \phi^{\mathrm{lin}}(w^*) - \phi(\hat{\theta}(\vec{1})) =: \hat{\sigma}_\phi \hat{\mathscr{S}}_\alpha \quad \Leftrightarrow \quad \frac{\Delta}{\hat{\sigma}_\phi} \geq \hat{\mathscr{S}}_\alpha.$$

- The "signal" Δ is the smallest change that reverses your conclusion
- The "noise" $\hat{\sigma}_\phi^2 \to \mathrm{Var}(\sqrt{N}\phi)$ ("sandwich" variance estimator)
- The "shape" $\hat{\mathscr{S}}_\alpha \to$ a nonzero constant and is $\leq \sqrt{\alpha(1-\alpha)}$

Contrast with sampling variability.
A 95% CI is given by $\phi(\hat{\theta}(\vec{1})) \pm \frac{1.96}{\sqrt{N}} \hat{\sigma}_\phi$. We reject $\phi(\hat{\theta}(\vec{1})) + \Delta$ when

$$\phi(\hat{\theta}(\vec{1})) + \Delta \geq \phi(\hat{\theta}(\vec{1})) + \frac{1.96}{\sqrt{N}} \hat{\sigma}_\phi \quad \Leftrightarrow \quad \frac{\Delta}{\hat{\sigma}_\phi} \geq \frac{1.96}{\sqrt{N}}.$$

The **signal to noise ratio** $\frac{\Delta}{\hat{\sigma}_\phi}$ determines robustness to both data dropping and sampling variability, but with **different thresholds**.

What makes an analysis sensitive?

Robust to data dropping: ("dropping robustness")

$$\mathrm{SNR} := \frac{\Delta}{\hat{\sigma}_\phi} \geq \hat{\mathscr{P}}_\alpha$$

Robust to sampling variation: ("sampling robustness")

$$\mathrm{SNR} := \frac{\Delta}{\hat{\sigma}_\phi} \geq \frac{1.96}{\sqrt{N}}$$

- **Dropping robustness $\neq$ sampling robustness in general.**
Proof: $\hat{\mathscr{P}}_\alpha \neq \frac{1.96}{\sqrt{N}}$.

- **When the SNR is small, sufficiently large N produces sampling robustness, but not necessarily dropping robustness.**
Proof: $\frac{1.96}{\sqrt{N}} \rightarrow 0$, but $\hat{\mathscr{P}}_\alpha \rightarrow$ a nonzero constant.

- **Statistical insignificance is dropping non-robust for large N.**
Proof: Insignificance means $|\phi(\hat{\theta}(\vec{1}))| \leq \frac{1.96}{\sqrt{N}}\hat{\sigma}_\phi$.
$\Rightarrow$ A result can be made significant by a change of no more than $\frac{1.96}{\sqrt{N}}\hat{\sigma}_\phi$.
$\Rightarrow$ The SNR for a conclusion of "insignificance" is $\frac{\Delta}{\hat{\sigma}_\phi} \leq \frac{1.96}{\sqrt{N}} \rightarrow 0 \leq \hat{\mathscr{P}}_\alpha$.

- **P-hacking is dropping non-robust for large N.**
Proof: P-hacked effect sizes are of the order $\frac{1.96}{\sqrt{N}}\hat{\sigma}_\phi$.

What makes an analysis sensitive?

Robust to data dropping:
("dropping robustness")

$$\mathrm{SNR} := \frac{\Delta}{\hat{\sigma}_\phi} \geq \hat{\mathscr{P}}_\alpha$$

Robust to gross errors:
("gross error robustness")

Gross outliers cannot produce arbitrarily large changes to ϕ.

- **Dropping non-robustness is not driven by misspecification.**

Proof: Small Δ are dropping non-robust irrespective of specification.

- **Gross outliers primarily affect dropping robustness through $\hat{\sigma}_\phi$.**

Proof: For a fixed $\hat{\sigma}_\phi$, outliers decrease $\hat{\mathscr{P}}_\alpha$. (Details in paper.)

How to make an analysis less sensitive?

Robust to data dropping:
("dropping robustness")

$$\mathrm{SNR} := \frac{\Delta}{\hat{\sigma}_\phi} \geq \hat{\mathscr{P}}_\alpha$$

To achieve dropping robustness, reduce $\hat{\sigma}_\phi$ and / or increase Δ.
Proof: Across typical distributions, $\hat{\mathscr{P}}_\alpha$ varies little. (Details in paper.)

In the Mexico microcredit example,

$$\hat{\sigma}_\phi = 757.8 \qquad \phi(\hat{\theta}(\vec{1})) = -4.55 \qquad N = 16,560$$

The study overcame a very low signal to noise ratio with a very large N.

This (canonical) response to low signal to noise ratio — to gather more data — produces small SEs, but cannot produce dropping robustness.

Conclusion

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- We can quickly and automatically find an approximate influential set which is accurate for small sets.
- Data dropping robustness is principally determined by the signal to noise ratio, and captures sensitivity distinct from sampling and gross error sensitivity.

Links and references

Tamara Broderick, Ryan Giordano, Rachael Meager (alphabetical authors)
"An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Change Conclusions?"
https://arxiv.org/abs/2011.14999

Select blog posts with more details: `https://rgiordan.github.io`

- Data dropping sensitivity overcomes p-hacking
- Collinearity in OLS after dropping
- Influence functions and sums
- Connections to the bootstrap

Related software on `github`:

- rgiordan/zaminfluence (for `R`)
- rgiordan/vittles (for `Python`)

Some of my work on other forms of robustness:

- Prior sensitivity in Bayesian nonparametrics [Giordano et al., 2021]
- Model sensitivity of MCMC output [Giordano et al., 2018]
- Cross-validation [Giordano et al., 2019]
- Frequentist variances of MCMC posteriors (in progress)

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Extra slides

A simulation

For $N = 5,000$ data points, compute the OLS estimator from:

Regressors	Residuals	Responses
$x_n \sim \mathcal{N}(0, \sigma_x^2)$	$\varepsilon_n \sim \mathcal{N}(0, \sigma_\varepsilon^2)$	$y_n = 0.5 x_n + \varepsilon_n$

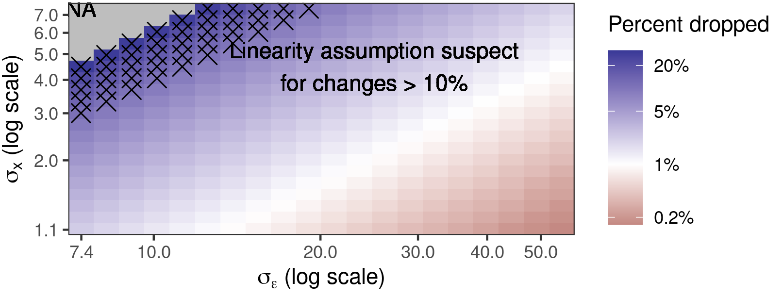

Figure: The approximate perturbation inducing proportion at differing values of σ_x and σ_ε. Red colors indicate datasets whose sign can is predicted to change when dropping less than 1% of datapoints. The grey areas indicate $\hat{\Psi}_\alpha = \mathtt{NA}$, a failure of the linear approximation to locate any way to change the sign.

Influence function

The present work is based on the *empirical influence function*. Consider:

- True, unknown distribution function $F_\infty(x) = p(X \le x)$
- Empirical distribution function $\hat{F}(x) = \frac{1}{N} \sum_{n=1}^{N} \mathbb{I}\left(x_n \le x\right)$
- A statistical functional $T(F)$.

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We estimate with $T(F_\infty)$ with $T(\hat{F})$.
Sample means are an example:

$$T(F) := \int x\, F(\mathrm{d}x).$$

Z-estimators are, too:

$$T(F) := \theta \text{ such that } \int G(\theta, x) F(\mathrm{d}x) = 0.$$

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Form an (infinite-dimensional) Taylor series expansion at some F_0:

$$T(F) = T(F_0) + T'(F_0)(F - F_0) + \mathrm{residual}.$$

When the derivative operator takes the form of an integral

$$T'(F_0)\Delta = \int \psi(x; F_0)\Delta(\mathrm{d}x)$$

then $\psi(x; F_0)$ is known as the *influence function*.
Where to form the expansion? There are at least two reasonable choices:

- The limiting influence function $\psi(x, F_\infty)$
- The empirical influence function $\psi(x, \hat{F})$

Influence function

- The limiting influence function (LIF) $\psi(x, F_\infty)$
  - Used in a lot of classical statistics [**??**Hampel, 1986, **?**]
  - Unobserved, asymptotic
  - Requires careful functional analysis [**?**]
- The empirical influence function (EIF) $\psi(x, \hat{F})$
  - The basis of the present work (also [Giordano et al., 2019, **?**])
  - Computable, finite-sample
  - Requires only finite-dimensional calculus

Typically the *semantics* of the EIF derive from study of the LIF.
Example: $\frac{1}{N}\sum_{n=1}^{N}(N\psi_n)^2 \approx \mathrm{Var}\left(\sqrt{N}\phi(\hat{\theta})\right)$.

But the EIF measures what happens when you perturb the data at hand.

Other data perturbations will admit an analysis similar to ours!

Local robustness

The present work is an application of *local robustness*. Consider:

- Model parameter λ (e.g., data weights $\lambda = w$)
- Set of plausible models $\mathcal{S}_\lambda$ (e.g. $\mathcal{S}_\lambda = W_\alpha$)
- Estimator $\hat{\theta}(x, \lambda)$ for data x and $\lambda \in \mathcal{S}_\lambda$ (e.g. a Z-estimator)

Global robustness: $\left(\inf_{\lambda \in \mathcal{S}_\lambda} \hat{\theta}(x, \lambda), \sup_{\lambda \in \mathcal{S}_\lambda} \hat{\theta}(x, \lambda)\right)$ (Hard in general!)

Local robustness: $\left(\inf_{\lambda \in \mathcal{S}_\lambda} \hat{\theta}^{lin}(x, \lambda), \sup_{\lambda \in \mathcal{S}_\lambda} \hat{\theta}^{lin}(x, \lambda)\right)$

...where $\hat{\theta}^{lin}(x, \lambda) := \hat{\theta}^{lin}(x, \lambda_0) + \left.\frac{\partial \hat{\theta}^{lin}(x, \lambda)}{\partial \lambda}\right|_{\lambda_0} (\lambda - \lambda_0)$.

Many variants are possible!

- Cross-validation [Giordano et al., 2019]
- Prior sensitivity in Bayesian nonparametrics [Giordano et al., 2021]
- Model sensitivity of MCMC output [Giordano et al., 2018]
- Frequentist variances of MCMC posteriors (in progress)